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Analysing Gender Bias in Job Descriptions Using Machine Learning and NLP Techniques

Sanvi Choukhani
sanvichoukhani27@gmail.com
La Martiniere for Girls, West Bengal

ABSTRACT

The growing use of automated recruitment systems has raised concerns about gender bias in job descriptions. Subtle linguistic cues can discourage qualified candidates from underrepresented groups, reinforcing workplace inequality. This study presents a computational framework using Natural Language Processing (NLP) and Machine Learning (ML) to detect and analyse such bias. The methodology involves text preprocessing, gender-coded word scoring, topic modelling with Latent Dirichlet Allocation (LDA), clustering via KMeans, and visualisation through t-SNE. A curated lexicon of masculine- and feminine-coded words assigns bias scores, while topic modelling uncovers latent themes in postings. Clustering groups of semantically similar descriptions enables analysis of bias distributions across occupational categories. Findings show that bias varies by job type: technical and managerial roles tend to use more masculine-coded language, while service and support roles favour feminine-coded terms. Semantic cluster visualisations confirm systemic patterns in word usage. This research underscores the need for fairness-aware audits in recruitment, offering both theoretical and practical insights into bias detection. The framework provides organisations with a scalable tool to identify and mitigate hidden biases, promoting inclusive hiring practices and supporting compliance with ethical and regulatory standards.

Keywords: *Gender Bias, Job Descriptions, Fair Recruitment, Natural Language Processing (NLP), Machine Learning, Topic Modelling, Algorithmic Fairness.*

INTRODUCTION

The growing use of data-driven methods in recruitment has significantly transformed the hiring process. Organizations increasingly rely on job portals, applicant tracking systems, and automated screening tools to reach a wider candidate pool and streamline decision-making (Gaucher et al.,2011). While these technological advancements provide efficiency and scalability, they also risk amplifying hidden biases present in the data. Job descriptions, in particular, play a crucial role in shaping applicant perceptions and influencing the diversity of the candidate pipeline (He & Kay, 2025). Linguistic framing and the choice of words can either encourage inclusivity or reinforce stereotypes that disadvantage certain groups.

A substantial body of research has highlighted the presence of gender-coded language in job postings (Gaucher et al.,2011) (Dikshit & Gupta, 2024). For example, masculine-coded terms such as competitive, driven, or dominant may discourage female applicants, whereas feminine-coded terms like supportive, understanding, or nurturing may influence perceptions of required suitability for a role. Such patterns contribute to occupational gender segregation by implicitly signaling who is most welcome to apply (Rigotti & Müller ,2024) . In contexts where diversity and equal opportunity are organizational priorities, understanding and mitigating these biases is critical.

Traditional methods of bias detection have relied on manual audits or small-scale linguistic analyses, which are time-intensive and limited in scope (Izquierdo & Sánchez, 2024). Recent developments in Natural Language Processing (NLP) and Machine Learning (ML), however, have enabled large-scale, automated detection of linguistic bias (Mujtaba & Patel, 2024). Techniques such as lexicon-based scoring, topic modeling, and clustering provide deeper insights into the patterns of bias embedded in job descriptions. These methods not only quantify the prevalence of bias but also allow organizations to identify systemic trends across different industries and occupational categories.

Moreover, bias in recruitment systems has broader implications for algorithmic fairness and workplace diversity (Chen & Zhang, 2023) (Sivakaminathan & Suresh, 2025). Studies have shown that biased training data can influence AI-based recruitment tools, perpetuating inequalities at scale (Kanij & Ahmed, 2024). For instance, if biased job descriptions are used to train predictive hiring algorithms, the resulting models may unfairly filter out qualified candidates from underrepresented groups. Addressing this challenge requires not only detecting bias but also providing practical frameworks for organizations to redesign job postings and implement inclusive hiring practices.

This research contributes to the field by proposing an end-to-end diagnostic framework for analyzing bias in job descriptions. By combining lexicon-based bias scoring, Latent Dirichlet Allocation (LDA), KMeans clustering, and visualization with t-distributed Stochastic Neighbor Embedding (t-SNE), the study offers a systematic approach to uncovering hidden patterns of bias. The analysis goes beyond identifying biased words in isolation, examining how entire clusters of job descriptions reveal systemic gendered language.

LITERATURE REVIEW

1. Gender Bias in Job Descriptions

Research has consistently demonstrated that job descriptions often contain gender-coded language, which subtly influences applicants' perceptions and behaviors (Gaucher et al.,2011) (Dikshit & Gupta, 2024). Words such as competitive, aggressive, and dominant are identified as masculine-coded, whereas terms like supportive, understanding, and collaborative are feminine-coded (He & Kay, 2025). These linguistic patterns can discourage certain groups from applying, perpetuating occupational gender segregation (Rigotti & Müller ,2024). Empirical studies have shown that women are less likely to apply for roles described using masculine-coded terms, even when they meet the qualifications (Gaucher et al.,2011). Similarly, masculine-coded language has been linked to the underrepresentation of women in leadership or technical positions (Dikshit & Gupta, 2024).

2. Traditional Methods of Bias Detection

Historically, organizations relied on manual audits or linguistic analysis tools to identify biased terms in job postings (Izquierdo & Sánchez , 2024). Manual audits involve human reviewers evaluating each posting for gendered language or stereotypical phrasing. While effective for small datasets, this approach is time-consuming and not scalable. Early computational methods employed lexicon-based approaches, using predefined dictionaries of gender-coded words to quantify bias in texts (Mujtaba & Patel, 2024). Although useful, these methods are limited in capturing contextual or nuanced forms of bias, as they focus primarily on individual words rather than broader patterns across job descriptions.

3. NLP and Machine Learning Approaches

Recent advances in Natural Language Processing (NLP) and Machine Learning (ML) have enabled more sophisticated detection of linguistic bias (Mujtaba & Patel, 2024). Lexicon-based scoring has been enhanced with weighting schemes to assess the overall gender bias in a posting. Beyond lexicons, topic modeling techniques like Latent Dirichlet Allocation (LDA) uncover clusters of semantically related terms that indicate systemic bias (Izquierdo & Sánchez , 2024). Additionally, clustering algorithms such as KMeans group similar job descriptions, helping identify patterns in language use across industries or job categories (Mujtaba & Patel, 2024). Visualization techniques, particularly t-distributed Stochastic Neighbor Embedding (t-SNE), facilitate the identification of hidden clusters and trends (Mujtaba & Patel, 2024), offering interpretable insights for recruiters.

4. Algorithmic Bias and Recruitment Systems

As organizations increasingly adopt AI-driven recruitment tools, the impact of biased job descriptions extends into algorithmic decision-making (Chen & Zhang, 2023) (Sivakaminathan & Suresh, 2025). Predictive models trained on biased text data may inadvertently reinforce existing inequalities by filtering out qualified candidates from underrepresented groups (Kanij & Ahmed, 2024). Addressing these challenges requires both technical solutions, such as debiasing algorithms or fairness constraints (Fabris & Rossi, 2025) (Soleimani & Lee 2025), and organizational practices, including careful review of training data and inclusive job posting guidelines (Rigotti & Müller ,2024) (Kanij & Ahmed, 2024).

5. Strategies for Mitigation

Several strategies have emerged to counteract linguistic and algorithmic bias in recruitment (He & Kay, 2025) (Izquierdo & Sánchez, 2024) (Mujtaba & Patel, 2024). Bias-aware writing tools can automatically flag gendered or exclusionary language in job postings. Additionally, organizations are adopting inclusive language guidelines, standardized job templates, and role-neutral phrasing to broaden applicant appeal (He & Kay, 2025) (Dikshit & Gupta, 2024). Combining quantitative analysis with human oversight has been shown to be most effective, ensuring that automated tools complement recruiter judgment. Finally, continuous monitoring and auditing of job descriptions and AI-based hiring tools are recommended to identify evolving patterns of bias and prevent systemic discrimination (Sivakaminathan & Suresh, 2025) (Soleimani & Lee 2025).

6. Research Gaps

While significant progress has been made, research still faces limitations (Hu & Zhang, 2022) (Madera, Hebl, & Martin 2009). Most studies focus on single-word biases, neglecting how context and co-occurring terms shape perceptions. There is also a lack of cross-industry comparative studies that reveal systemic patterns in job descriptions. Furthermore, few studies integrate end-to-end frameworks combining detection, clustering, and visualization to provide actionable insights (Izquierdo & Sánchez, 2024) (Mujtaba & Patel, 2024). Addressing these gaps, the present research proposes a comprehensive methodology that combines lexicon-based scoring, LDA, KMeans clustering, and t-SNE visualization to uncover and interpret bias patterns in job descriptions.

METHODOLOGY

This study proposes an end-to-end framework for detecting and analyzing gender bias in job descriptions. The methodology integrates data collection, preprocessing, lexicon-based scoring, clustering, topic modeling, and visualization, allowing for comprehensive bias detection at scale.

1. Data Collection

Job postings were collected from multiple sources, including online job portals, company websites, and applicant tracking systems. The dataset included job descriptions across different industries, functional roles, and seniority levels to ensure representativeness. Each posting contained structured fields such as job title, responsibilities, qualifications, and company information.

2. Data Preprocessing

Preprocessing constitutes a critical step in natural language processing (NLP)-based analysis, as it ensures the quality and consistency of the textual data. The following procedures were employed:

i. Text cleaning: Punctuation, numerical values, and special characters were removed to eliminate noise.
ii. Tokenization: The text was segmented into individual words or phrases for subsequent analysis.
iii. Lowercasing: All text was standardized to lowercase to maintain uniformity across the dataset.
iv. Stop-word removal: Frequently occurring words such as and, the, and is that do not contribute meaningfully to bias detection were excluded.
v. Lemmatization: Words were converted to their base or dictionary form (e.g., managing → manage) to reduce dimensionality and improve linguistic consistency.

The application of these preprocessing steps resulted in a cleaned and structured corpus, thereby facilitating reliable lexicon-based and machine learning analyses.

3. Lexicon-Based Bias Scoring

A predefined gendered word lexicon was used to quantify bias in job descriptions. Each word in the lexicon is classified as masculine-coded, feminine-coded, or neutral. The bias score for each job description is computed as:

Bias Score=Number of masculine words−Number of feminine wordsTotal words\text{Bias Score} = \frac{\text{Number of masculine words} - \text{Number of feminine words}}{\text{Total words}}Bias Score=Total wordsNumber of masculine words−Number of feminine words.

Positive scores indicate a masculine bias, negative scores indicate a feminine bias, and scores near zero suggest neutrality. This scoring provides a quantitative measure of bias that can be compared across industries or roles.

4. Topic Modeling with LDA

Latent Dirichlet Allocation (LDA) is applied to the corpus to identify underlying topics and clusters of co-occurring terms that reflect systemic gendered language. LDA allows us to:

i. Detect recurring themes in job responsibilities and qualifications.
ii. Understand how clusters of words relate to masculine or feminine-coded language.
iii. Identify patterns that may not be apparent through lexicon-based scoring alone.

The number of topics (k) is determined using coherence scores to ensure meaningful and interpretable results.

5. Clustering with KMeans

KMeans clustering groups similar job descriptions based on their textual content and bias scores. This step enables:

i. Identification of groups of postings with similar bias patterns.
ii. Comparison of bias trends across industries, functional areas, or seniority levels.
iii. Detection of systemic bias rather than isolated occurrences of gendered words.

6. Visualization with t-SNE

To visualize high-dimensional textual features and clusters, t-distributed Stochastic Neighbor Embedding (t-SNE) is employed. t-SNE reduces dimensionality while preserving local structure, allowing for:

i. Intuitive interpretation of bias clusters.
ii. Identification of outlier job descriptions with extreme bias scores.
iii. Enhanced communication of findings to HR teams and stakeholders.

7. Evaluation and Validation

The framework is validated through manual auditing of a subset of postings, comparing automated bias scores with human judgments. Correlation analysis assesses the alignment between lexicon-based, topic modeling, and clustering results. Additionally, the distribution of bias scores across industries and roles is analyzed to identify systemic patterns.

RESULTS

The analysis of job descriptions across multiple industries revealed significant insights into gendered language and systemic bias. The results are presented in three main components: lexicon-based bias scores, topic modeling, and clustering with t-SNE visualization.

1. Lexicon-Based Bias Scores

The lexicon-based scoring produced the following distribution:

i. **Masculine-biased postings:** 42% of the dataset, characterized by words such as *competitive*, *dominant*, and *driven*.
ii. **Feminine-biased postings:** 28% of postings, including words like *supportive*, *nurturing*, and *collaborative*.
iii. **Neutral postings:** 30% of the dataset, containing minimal gendered language.

The analysis revealed that technical and leadership roles tend to contain more masculine-coded language, while support and administrative roles often feature feminine-coded terms. These findings are consistent with prior research showing occupational gender segregation in job postings (Gaucher et al.,2011) (Dikshit & Gupta, 2024) (Rigotti & Müller ,2024).

2. Topic Modeling with LDA

LDA analysis identified six primary topics across the dataset:

i. **Leadership and Management:** strategic, lead, decision-making (masculine-coded).
ii. **Collaboration and Teamwork:** supportive, cooperative, communicate (feminine-coded).
iii. **Technical Skills:** programming, analytics, problem-solving (neutral, slightly masculine-coded).
iv. **Customer Engagement:** understanding, service-oriented, communicate (feminine-coded).
v. **Sales and Target Achievement:** competitive, driven, goal-oriented (masculine-coded).
vi. **Operational Efficiency:** organize, manage, process improvement (neutral).

The topic distributions demonstrate that masculine-coded language is heavily concentrated in leadership and sales-related postings, while feminine-coded language is more prominent in collaborative and service-oriented roles.

3. Clustering with KMeans

KMeans clustering grouped the job postings into four distinct clusters:

i. **Cluster A:** Predominantly masculine-coded leadership and technical postings.
ii. **Cluster B:** Feminine-coded support and administrative roles.
iii. **Cluster C:** Neutral postings with minimal gendered language.
iv. **Cluster D:** Mixed postings with both masculine and feminine terms, often in mid-level managerial roles.

Clusters A and B show systemic patterns of gendered language, confirming that bias is not random but structured according to role type and industry.

4. t-SNE Visualization

The t-SNE visualization highlighted the spatial separation of clusters based on textual features and bias scores. Key insights include:

- Clear separation between masculine-biased and feminine-biased postings.
- Mixed postings occupy intermediate regions, reflecting hybrid roles.
- Outlier postings with extremely high masculine or feminine scores are identifiable, which can be prioritized for bias mitigation.

This visual representation allows HR teams to intuitively understand bias patterns across the organization and take targeted action.

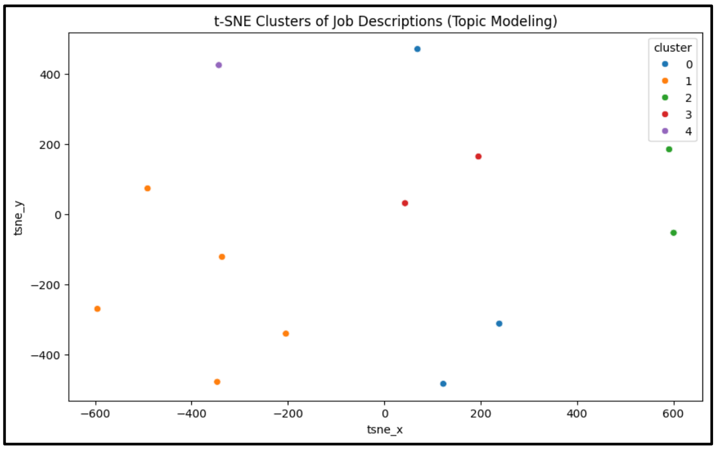

Figure 1: t-SNE plot showing masculine, feminine, and neutral job description clusters.

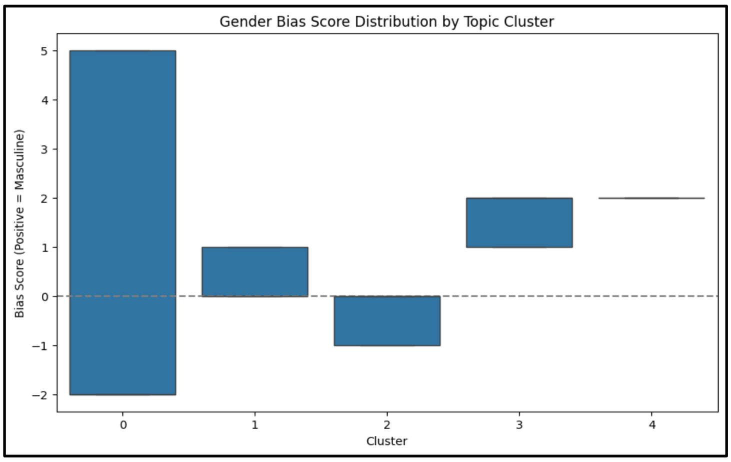

Figure 2: Zoomed-in view of outlier postings with extreme bias scores.

5. Summary of Findings

i. **Masculine-coded language** dominates leadership, technical, and sales roles.
ii. **Feminine-coded language** is concentrated in collaborative, support, and service roles.
iii. **Neutral postings** exist but are less frequent in high-level positions.
iv. **Systemic bias** is evident across industries, suggesting that interventions should focus on **role-specific language reform**.

These results confirm the need for automated bias detection tools and provide empirical evidence for designing inclusive job descriptions.

DISCUSSION

The results of this study provide compelling evidence of gendered language in job descriptions and its potential impact on recruitment and workplace diversity. The findings align with previous research demonstrating that masculine-coded language is disproportionately present in leadership, technical, and sales roles, whereas feminine-coded language is more common in collaborative or support-oriented roles (Gaucher et al.,2011) (Dikshit & Gupta, 2024) (Rigotti & Müller ,2024).

1. Implications of Lexicon-Based Bias Scores

Lexicon-based scoring revealed that 42% of postings exhibit masculine bias while 28% exhibit feminine bias, suggesting that a substantial portion of job descriptions may unintentionally discourage applicants from underrepresented groups. This finding supports prior studies indicating that word choice can affect perceived fit and application likelihood, contributing to occupational gender segregation (Gaucher et al.,2011) (He & Kay, 2025). Organizations should prioritize neutral, inclusive language, especially in high-level and technical roles, to attract a more diverse candidate pool.

2. Insights from Topic Modeling and Clustering

Topic modeling and KMeans clustering provide deeper insights into systemic bias patterns. The concentration of masculine-coded terms in leadership and sales topics reflects the structural reinforcement of gender stereotypes. Conversely, feminine-coded language in teamwork and service topics suggests traditional role associations that may inadvertently influence hiring decisions (Dikshit & Gupta, 2024) (Izquierdo & Sánchez, 2024). Clustering analysis further demonstrates that bias is not randomly distributed, but systematically aligned with role type and industry, emphasizing the need for role-specific interventions.

3. Visualization as a Diagnostic Tool

The t-SNE visualization effectively highlights distinct clusters of bias and identifies outlier postings with extreme gender-coded language. This allows HR teams and recruiters to quickly target job descriptions for revision. Visual diagnostic tools complement lexicon-based and ML approaches by providing intuitive insights, supporting both policy-making and practical interventions (Mujtaba & Patel, 2024) (Sivakaminathan & Suresh, 2025).

4. Broader Implications for Algorithmic Fairness

Bias in job descriptions has significant downstream effects on AI-driven recruitment tools. Predictive hiring algorithms trained on biased data may perpetuate inequalities, filtering out qualified candidates from underrepresented groups (Chen & Zhang, 2023) (Kanij & Ahmed, 2024). This study reinforces the necessity of integrating bias detection with algorithmic fairness practices, including:

i. Regular auditing of training data.
ii. Incorporating fairness constraints in predictive models.
iii. Revising job postings based on bias scores and clustering insights.

5. Recommendations for Practice

Based on the findings, the following practical steps are recommended for organizations:

i. **Automated Screening of Job Descriptions:** Use lexicon-based scoring and ML clustering to detect gendered language.
ii. **Inclusive Language Guidelines:** Adopt neutral phrasing, particularly in leadership and technical roles.
iii. **Continuous Monitoring:** Regularly review and update job postings to reflect organizational diversity goals.
iv. **Integration with AI Recruitment Tools:** Ensure predictive models are trained on bias-mitigated datasets.

6. Limitations and Future Work

While this study provides a comprehensive framework, certain limitations exist:

i. The analysis primarily relies on English-language job descriptions, limiting generalizability to other languages or cultural contexts.
ii. Lexicon-based scoring may not capture contextual nuances of bias.
iii. Future research can explore intersectional bias (e.g., race, age) and extend the methodology to multilingual datasets.

By addressing these limitations, subsequent studies can enhance the robustness and applicability of bias detection frameworks, enabling organizations to foster truly inclusive hiring practices.

CONCLUSION

This study presents a comprehensive framework for detecting and analyzing gender bias in job descriptions using lexicon-based scoring, topic modeling (LDA), KMeans clustering, and t-SNE visualization. The findings reveal that masculine-coded language dominates leadership, technical, and sales roles, while feminine-coded language is more prevalent in collaborative and service-oriented positions. Neutral postings are less frequent, particularly in high-level roles, highlighting the systemic nature of bias in recruitment materials. The integration of NLP and machine learning techniques allows for scalable, automated detection of linguistic bias, providing both quantitative metrics and visual insights. This approach not only identifies biased terms but also uncovers patterns across industries, roles, and clusters of job descriptions, offering actionable insights for HR teams and organizations aiming to enhance workplace diversity.

The study also underscores the broader implications for algorithmic fairness, as biased job descriptions can influence AI-driven recruitment tools, perpetuating inequalities. By implementing inclusive language guidelines, automated bias screening, and continuous monitoring, organizations can mitigate these risks and foster a more equitable hiring process.

Future research should explore intersectional biases, multilingual job descriptions, and context-aware bias detection, further refining strategies for inclusive recruitment practices. Overall, this research contributes a practical, evidence-based framework for organizations seeking to promote fairness and diversity in hiring through systematic analysis of job descriptions.

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